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The effect of simple vs. complex training upon binary predictions

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THE EFFECT OF SIMPLE VS. COMPLEX TRAINING UPON BINARY PREDICTIONS

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In a binary prediction paradigm, 96 Ss were trained on either a simple or complex sequence the basic units of which were runs of events rather than single events. The runs were of lengths two and five for half of the Ss and four and five for the other half. The purpose of this training was to induce the Ss in each group to track simple or complex hypotheses concerning the orderings of the runs.

Half of the Ss in each of these four groups were transfered to a sequence made by essentially randomly ordering the two run lengths present in training. Error data was collected for these Ss in transfer and for all Ss in training for all run lengths. Two types of errors associated with specific run lengths were distinguished.

The other half of the Ss were transfered to an all-correct condition in which all responses were called correct. Sequences of predictions from these

Ss were classified simple (S), complex (C) or other (O) to determine whether the differential training had been successful.

An information processing model of sequential choice behavior was presented. Ss were viewed as performing all of the tasks necessary in a limited capacity buffer. The processes sharing the buffer were seen as sharing time with one another such that the increased activity of any one could overflow capacity and disrupt the others.

Results indicated that the differential training had been successful. Groups trained on simple sequences were found to have higher Type [illegible] error rates in transfer than groups trained on complex sequences, contrary to expectation. Also a predicted interaction of error type with type of training was not found to be present in the transfer. The data did support the notion that Ss tracking complex hypotheses shift their attention to Type A error points causing increases in error rates at Type [illegible] error points. An explanation for the observed relationships between error rates among groups was proposed.

Latency data was also collected, but showed few consistencies. Reaction times were greater for groups with simple than for groups with complex training. The curve of latencies for various run lengths was the same for 2 - 5 and 4 - 5 groups indicating a factor working independently of run variability.

INTRODUCTION

In the typical probability learning experiment a Ss is asked to predict which of two events will occur on each of a number of trials. The two events are, with varying restrictions, randomly ordered. Due to the many patterns which arise, such a procedure has inherent in it a problem of stimulus identifiability. It is therefore very difficult in this context to study encoding, memory, hypothesis behavior or any of the other functions which might occur in the processing of sequential binary information.

For this and other reasons some investigators, in recent years, have used structured sequences of events to study sequential choice behavior in humans (Gambino & Myers, 1967; Restle, 1967; Rose & Vitz, 1966.) These sequences were made up of event patterns, for example the ordering of runs of lengths two and five of the two events, as the basic unit of the sequence instead of individual events.

Sequences structured in this way are, at least partially, learnable and the errors made can be classified into two distinct types. Take for example a sequence comprised of runs of events of lengths two and five. Once a S learns that there are only runs of length two and five it is possible for him to predict perfectly anytime except when he has seen exactly two events in a row. In this case he may not know whether the run will break off and be of length two, or continue and be of length five. This point is called the uncertainty point. Predictive behavior at this point is dependent upon such factors as the run contingencies, learnability of the sequence, and the memory capacity of the *S*. Errors at the uncertainty point will be referred to as Type A errors.

The second type of error, which will be referred to as Type B errors, occurs at those positions where it is theoretically possible to predict correctly all of the time once the run lengths present are known. Type B errors can be broken down into two subtypes. The first, an anticipatory error, is defined as the prediction of an event alternation when a repetition has a probability of 1 of occurring. In the example anticipatory errors can occur when the *S* has seen either one, three or four events in a row. The second subtype, a perseverative error, is defined as the prediction of an event repetition when an alternation has a probability of 1 of occurring. In the example perseverative errors can occur only when the *S* has seen five events in a row.

These Type B errors have been found to be present in some *Ss* after many hundreds of trials and their rate of occurrence is highly dependent upon such characteristics of the sequence as the number and lengths of event runs used in its construction.

Some theories which have been proposed to account for these Type B errors make use of either a count loss or a miscounting notion. In the count loss view an S may forget whether he has seen, say, four or five events in a row. He then enters a guessing state in which he may make an error either immediately or later in the same run. It is this uncertainty as to the position of the predictive error in relation to the counting error which makes quantitative predictions difficult. This is similar to the count loss theory proposed by Myers (1970). Myers' position is that when S loses count he has no cues as to where he is in the run. He then guesses until he picks up the correct count at the beginning of the next run. Evidence to date indicates that Ss rarely gain but are most likely to drop counts and rarely more than one (Ellis & Myers, manuscript in preparation). This implies that although a processing error has been made Ss still retain some information about the current run.

The miscounting theory (Myers, 1970) says that S makes an unconscious error which may occur at any of several phases of the processing task. He may fail to register or encode the sequential information correctly at input. The information may become distorted later while residing in a short term memory buffer. Or it may be retrieved incorrectly. Here again because of the uncertainty as to the place of the error is the sequence of the stage of necessity at which the error occurs, quantitative predictions are difficult. For one attempt at such predictions assuming errors due to run length generalization, see Gambino & Myers (1967).

While these theories propose various mechanisms to describe how and where errors may occur, they cannot tell us why these errors should occur when they do. So the question still remains, why should anticipatory and perseverative errors persist in some Ss after many trials?

The answer considered here concerns the mechanisms by which a S keeps track of the current run length. This counter mechanism is one of a number of information processing units which exist in a fixed capacity memory buffer. The counter is subject to failure only very rarely due to direct input. Instead most failures are due to input to one of the other processes sharing the buffer. It is to a discussion of these interactions which we now turn our attention.

Soller & Myers (Manuscript in preparation) collected predictive protocols under an all-correct reinforcement phase during which Ss were reinforced as correct regardless of which prediction they made. This procedure yielded sequences of predictions which were classified as simple or complex based upon their reflection of the S's hypothesis concerning the complexity of the sequence.

A direct relationship was found between hypothesis complexity and Type I error rates in the preceding acquisition phase.

In analyzing this relationship it is necessary to keep in mind all that the S's task entails. He must register the occurrence of events, encode them into an internal representation of the ongoing pattern, retain this information in temporary or short term memory, generate a prediction based on the information in memory, and his knowledge of the outcomes associated with the same pattern in the past, note the consequences of his prediction, and generate new hypotheses consistent with information stored in memory. If S's information processing system is of a fixed capacity, the fluctuations in activity of any of these processes must necessarily have effects upon the others. The whole process can be thought of as analogous in many respects to a computer time-sharing system.

In respect to the relationship mentioned earlier, more complex hypotheses place heavier demands upon some of the processes sharing time in the system. Looking at the nature of the sequences we can see why this is so. Simple sequences, or hypotheses, necessitate S to hold in memory only the immediately preceding run length in addition to keeping the current run length count. Complex sequences require the storage and utilization of much greater quantities of information and therefore should displace more activity in the fixed capacity buffer than the simpler sequences. It is therefore expected that Ss tracking more complex hypotheses should be more likely to make counting errors and so their Type B error rates should be higher than those Ss tracking simpler hypotheses.

In the Colker & Myers study, complex solvers tended to be Ss with high Type B error rates in acquisition while simple solvers tended to have lower Type B error rates. If the analysis of this relationship is valid it should be possible to induce this effect. That is, if Ss could be induced to track complex hypotheses, they should produce higher Type B error rates than Ss induced to track simpler hypotheses. It is this effect which the present study hoped to produce.

The expectancy of a simple or complex sequence had to be differentially induced in two groups of Ss. One group, the simple group, learned a simple alternation of run lengths requiring only the preceding run length to be held in memory in order to predict the sequence perfectly. The second group, the complex group, learned a sequence comprised of a double alternation of runs followed by two single alternations requiring as many as the five preceding run lengths to be held in memory in order to predict the sequence perfectly. Each of these groups was then transferred to a sequence generated by the essentially random ordering of the two lengths present. (Computer memory limitations necessitated a repeating sequence, but it was of sufficient length to be considered for all intents and purposes random.) A record was kept of all responses. It was predicted that more errors would occur on the average in the complex than in the simple groups during transfer.

If tracking complex hypotheses means paying more attention to the ordering of runs and therefore displaying activity from other time sharing processes such as counting, we would expect to find an interaction of Type A and Type B errors with complexity of hypothesis being tracked. That is, if an error were due to miscounting then it would be equally likely to occur at any point in the sequence. If it were due to processing activity being spent on tracking complex hypotheses and therefore impairing S's ability to keep track of the current run length, then the error rates at Type B error points would increase while performance at the uncertainty point would remain at chance level. This shifting of attention to the uncertainty point (e.g., tracking more complex hypotheses) is under S control. If, however, some factor not under S control were operative in the situation which effected the entire information processing system we would expect both types of errors to be effected similarly.

Another prediction, and crucial test for the results of the transfer phase, regards the success of the differential training phase. The object of the training was to induce the complex group to track more complex hypotheses than the simple group. To test this an all-correct reinforcement schedule was employed like that used by Mellott (1969) and Colker & Myers. Half of the Ss in each of the training groups were transferred, not to the random sequence, but to an all-correct reinforcement phase. It was predicted that more complex solutions would be present in the complex group's all-correct protocols than in the simple group's.

Because the run lengths present in a sequence has been found to be a powerful determinant of Type B error rates (Butler, Myers & Myers, 1969; Myers, Butler & Olson, 1969) these were also manipulated in the present study.

Method

Subjects - The Ss were 96 undergraduates from the University of Massachusetts fulfilling course requirements. Participation was for a session lasting about 45 minutes including a 10 to 15 minute debriefing. The Ss were assigned to the eight groups randomly, 12 Ss in each group.

Apparatus - Ss were run in a soundproof room containing four booths separated by wooden partitions. Each booth contained a chair, section of table, and a wooden console. The consoles were low grey boxes with 11 1/2 inch square bases and sloping faces. On each face were six response button and green reinforcement light pairs arranged in a semicircle with a home button at their center. Only the two end button and light pairs were used. The starting signal used was a zero in the middle field of a three field digital NIXIE display mounted about three feet high on the wall about seven feet in front of the booths. Conversation in the experimental room was monitored with an intercom.

Ss were run completely independently with sequences controlled and responses recorded by a Digital PDP8/I computer. A prediction was made on each trial by pressing one of the two response buttons at either end of the semicircle. One of the two corresponding reinforcement lights was then illuminated for one second with the extinction of this light marking the beginning of the next trial. The beginning of the training and transfer phases of the experiment were marked by the extinction of the zero in the NIXIE display.

Procedure - Anywhere from one to four *Ss* were run at a time with each *S* individually paced. *Ss* were led into the experimental room and allowed a few minutes to become settled while *E* initialized the computer for the session. The *E* then read the *Ss* the following instructions:

In this experiment you will be asked to predict which of two lights will come on. On the panel in front of you are six button and light pairs arranged in a semicircle. We will be concerned only with the pairs at the ends, the first button and light on the left and the sixth button and light on the right. Ignore the other four pairs and the button in the center. These are being used in other experiments currently being run in this same room. Also ignore the tags which say yes-no or true-false. These are also being used in the other experiments.

After I leave the room watch this (indicating NIXIEs) light. It will be used to signal the beginning of the session only. When it goes off the experiment will begin. You should then ignore it for the remainder of the session. It is just to let you know that I have started the computer and it is ready to record your predictions. You should then press the button on your panel, either the first or the sixth, corresponding to the light which you believe will light up. Push the button firmly and release it quickly. Don't hold the button down, because the computer may not record your prediction correctly. After you have made your prediction one of the two lights will come on indicating to you whether your prediction was right or wrong. Try to predict as accurately as possible which light will appear. As soon as the light on the panel goes off you may make your next prediction, and so on. Ignore the others in the room during the session. You will each be doing something different so if someone else is taking longer or shorter than you it is probably for just this reason so don't pay it any attention.

There will be two parts to this experiment. When you finish the first part the light in the third position on your panel, just left of center, will come on. When this happens stop making predictions and relax. When everyone has finished I will come in and get you started on the second part.

You may take your time in responding, but try to make your predictions as quickly as possible. Do not talk to the others at any time during the experimental session. Before we start, are there any questions? O.K. remember, when you make your predictions push the buttons down firmly and release them quickly. Don't hold them down. Try to predict as accurately as you can which of the two lights will appear. All right, we are ready to begin then. Make your first prediction as soon as these lights (indicating NIXIEs) go off. Good luck!

Any questions were answered by paraphrasing the instructions as closely as possible. E then left the room closing the door and activated the computer.

At the end of the first half of the session E re-entered the room telling the Ss to relax for a few minutes, without talking, while the computer was readied for the second part of the experiment. When the computer was ready E read the Ss the following:

> The instructions for the second part of the experiment are the same as those for the first. The sequence of lights will be different, but again you should try to predict as accurately as possible which light will appear. When everyone is done I'll come in and explain what the experiment was all about, tell you how you did, and give you your credit. We are now ready to begin the second part. Make your first prediction as soon as this light (indicating [illegible]) goes off. Good luck!

E then left the room as before and the second session was completed. A short debriefing period followed.

Design - Sequences were constructed of runs of left or right hand lights of lengths two and five or four and five. During the first session Ss learned either simple or complex sequences and during the second had either a random or an all-correct reinforcement schedule yielding the basic 2x2x2 design. In the remainder of this paper the notation shown in Table 1 will be used in referring to the treatment levels of any of the eight groups.

Insert Table 1 about here

Sequences - In the first session simple and complex sequences were used. The simple sequences were made up of a single alternation of the two run lengths present. The period of such sequences was two runs or seven trials for the 2-5 groups and nine trials for the 4-5 groups. Criterion was 350 trials or two consecutive periods correct. The complex sequences were made up of one double alternation of run lengths followed by two single alternations for a period of eight runs or 28 trials for the 2-5 groups and 36 trials for the 4-5 groups. Criterion was 350 trials or eight consecutive runs, one period, correct.

In the second session again two kinds of reinforcement schedules were used. Random sequences were made up of 12 runs, six short and six long, such that there were never more than three runs of the same length occuring in succession. Three different sequences of this type were used with the number of switches from long to short runs equated. Criterion was 350 trials or 12 consecutive runs, one period, correct. The all-correct schedules reinforced as correct whichever response S made. Criterion was 350 trials.

Results

Some preliminary tests were done on the training data to check for homogeneity between the groups transferred to random sequences and those transferred to all-correct. A *t* test was done for each of the four pairs for Type B and total error data. The results are shown in Table 2. One

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Insert Table 2 about here

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pair, the 2-5/s, differed significantly based on only the Type B error data.

Response protocols under all-correct were recorded for each of the 4[illegible] _S_s in the all-correct condition, half having had training on a simple sequence and half on a complex sequence. Six graduate students including the _E_ classified each of the protocols into one of three categories. They were: S - the protocol reflected a simple sequence of predictions (e.g., the sequence required only the immediately preceding run length to be held in memory in order to be predicted correctly); C - the protocol reflected a complex sequence of predictions (e.g., the sequence required more than the immediately preceding run length to be held in memory in order to be predicted correctly); O - the protocol did not reflect a _S_ generated hypothesis as to the nature of the sequence. These included _S_s who adopted wait and see strategies such as perseverating on the previous event until such time as some order or pattern could be deduced. All S and C protocols displayed event runs as the basic unit of the sequence. Any sequence consisting of all left or right hand predictions was classified O. Pearson correlation coefficients were calculated for all pairs of raters. These appear in Table 3. All correlations were high,

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Insert Table 3 about here

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the lowest being .[illegible]5 and the mean correlation was .[illegible].

All but the lowest were significant at the .01 level for a two tailed test, the lowest being significant at the .02 level.

The mean number of protocols classified in the S, C, and O categories as a function of type of training sequence are presented in Table 4. Also given are the numbers in each category based on the majority or modal rating.

Insert Table 4 about here

S and O protocols were grouped together to provide a test of the hypothesis that there would be more complex solutions under all-correct for those Ss trained on complex sequences than for those trained on simple sequences. A Phi coefficient with 46 degrees of freedom was calculated for the frequencies presented in Table 5. A negative correlation of -.267 which is significant at the .05 level

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Insert Table 5 about here

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for a one tailed test was obtained confirming the hypothesis.

To test the hypothesis that Ss trained on a complex sequence should make more errors than those trained on a simple sequence, an analysis of variance was done on the 2 x 2 data matrix for type of training sequence by run lengths present. The results, shown in Table 6, show that neither the type of training sequence ($F(1,44) = .247$) nor the run

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Insert Table 6 about here

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lengths present ($F(1,44) = 3.0$[illegible]) main effect was significant. However, the interaction was significant at the five percent level ($F(1,44) = 4.44$, $p < .05$). The hypothesis was disconfirmed, the type of training main effect almost reaching significance in the nonpredicted direction.

To find out if there was an interaction of error type with complexity of hypotheses tracked, each S's all-correct protocol was designated B, C or O on the basis of the rating received by the majority of the six raters (see Table 4, consensus). The percentages of possible Type A and Type B errors in training were calculated for each S and an analysis of variance done on the two factor data. The results showed a significant effect due to error type, $F(1,54) = 50.65$, $p < .001$. The solution type effect and the error type x solution type interaction were both insignificant, $F(1,54) = .0207$; $F(1,54) = .013$[illegible]. The data, means and standard deviations (in parentheses) of percentages of possible Type A and Type B errors as a function of solution type and training, are presented in Table 7. The number of

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Insert Table 7 about here

Ss in each cell is given under frequency. For B and C solvers the percentage of errors is less for Ss with complex training than for those with simple training. For the C solvers, however, this trend is reversed with the complex trained Ss having the higher error rates.

Latency data was collected and analyzed, but there were few consistent findings. Separate analyses were done for 2-5, 4-5, training and transfer groups, with trial 1 omitted from all analyses. The results of the analyses of variance for effects due to type of training (simple vs. complex), position in the current run (S having seen 1, 2, 3, 4, or 5 events in the run), and type of response (error vs. correct) are presented in Table 8. Latencies were longer for error than for correct

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Insert Table 8 about here

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responses in all but the 4-5 transfer group. Reaction times for groups with simple training were consistently greater than for those with complex training. Position in the run shows the most consistent effect. The position effect data are presented in Table 9. Latencies start

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Insert Table 9 about here

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high in the first position and reach their lowest value in the second, except for the 2-5 transfer group where the low is reached in the third position. The times then increase monotonically over the remaining positions.

The position by response type interaction, significant in the 4-5 transfer group, is present to some extent (particularly over the first two positions) in all groups. The effect is due to a sharp convergence of the error and correct latencies over the first three positions.

Discussion

It may prove helpful at this point to review the information processing system proposed earlier and to see what light the results of the present study shed upon it.

It was proposed that the processing system works within a fixed capacity buffer. Many activities operate in a time sharing relation to each other such that the increased activity of any one of them must necessarily result in the displacement of the processing activity of one or more of the others. If the relative activities of the processes in the system are under Ss' control, then an interaction of error type with hypothesis complexity should be evident. If these activities are not S controlled, then Type A and Type B error rates should not differ as a function of hypothesis complexity. The factors which result in an overloading of the processing buffer should result in increases in Type B error rates over those recorded in situations in which those factors were absent.

The results of the present study have proved contradictory to some of these expectations. Ss showed fewer Type A and Type B errors in transfer when trained on complex rather than simple sequences, instead of more as predicted. The absence of the interaction between the two error rates and solution type suggests one of two explanations. One, the factors at work may not be S controlled. They may be imbedded in the complexity of the sequences themselves. Two, the Type B error rates show relatively large increases from S to C solvers as compared to the increases for the Type A rates (a ratio of 4.59 to 1 although both are statistically nonsignificant). The absence of the interaction seems to revolve around the slight increase in Type A error rates.

The hypothesis is that Ss trained on complex sequences attend more to the ordering of run lengths and therefore concentrate their attention at the uncertainty point. In transfer, sequences were essentially unlearnable and so performance at this point would necessarily remain at the chance level. It is, therefore, impossible to determine from transfer data whether the performances at this point reflect the proposed increased attention from complex trained groups. That is, if learning at this point is accomplished in an all-or-more fashion, we would learn nothing from looking at transfer error rates. However, if we were to look at the performance of the differentially trained groups on learnable sequences, we would expect to find faster learning rates at the uncertainty point for complex trained groups. Fortunately, the acquisition data are suitable for such an analysis. An increase in the learning rate at the uncertainty point for trials prior to the trial of last error would not, however, be reflected in the chance error rates. Instead, we would expect the trial of last error to occur sooner for those Ss displaying C solutions later under all-correct. The mean trial of last error at the uncertainty point for Ss giving S and C solutions under all-correct for 2-5 and 4-5 groups were: 2-5/S = 88.3, 2-5/C = 52, 4-5/S = 125.1, 4-5/C = 41. These figures lend qualitative support to the second interpretation, but care must be taken since they are based on extremely small n's of 6, 1, 6, and 1 respectively.

This analysis is somewhat complicated by the results in Table 7. Ss trained on complex sequences had, on the average, lower error rates in training than those trained on simple sequences. Looking at the S and O columns of Table 7, this effect is not uniform across solution types. Both Type A and Type B error rates decrease from the simple to the complex trained groups. In the C row the reverse is true, the rates increasing from the simple to the complex groups. The S and C columns in the complex trained group are analogous to the Ss in the Colker & Myers study. Here again, complex solvers make more errors than simple solvers replicating their results. Care must be taken as the number of Ss in the C column is small.

The differential effects of the sequence on the S and O as opposed to the C solvers might at first appear mysterious, but if we may hypothesize as to the nature of the Ss in each of these groups it may help us to see the factor or factors producing these reverses and the greater error rates for the complex over the simple solvers shown in Table 7. The first thing to note is that the error rates for the S and O groups are very close. Much closer than either is to the error rates for the C group. This does not necessarily mean that the same processes are at work in each group. In fact, just the opposite may be true. It does, however, imply that the sequences effect the working processes in the same way.

The S group is comprised of individuals who tracked simple solutions to the sequences under all-correct, after simple or complex training. It is suggested that these Ss ignore complex aspects of the sequence. They learn simple contingencies among runs and the more salient aspects of the higher order contingencies quite readily. But they cannot or will not extend themselves to the extent necessary to learn the complete complex sequence.

We would therefore expect reasonable performance on complex sequences, but no complex solutions under all-correct.

The O group is comprised of *S*s who do not display hypotheses concerning the nature of the sequence under all-correct. The majority seem to display more optical strategies like letting the sequence unveil itself without imposing their own biases upon it. These *S*s, like the S group, pick up less complex contingencies in the complex sequences and also do reasonably well on them. But somehow for their more objective approach they may lack the interest of the imagination to apply themselves completely to the task. And their approach would lead us to predict an absence of complex solutions under all-correct. In both of these cases the *S*s, for quite different reasons, would not allow an over extention of their efforts which would be likely to result in an overloading of the processing system. They would therefore have lower error rates than *S*s whose systems were overloaded.

The C solvers seem to be a part of the O group. This is evidenced by the equal numbers of C solvers in simple and complex trained groups while the C and O underwent a trade off (see Table 4). They might be viewed as applying themselves with less inhibitions than the O group and as being more realistic than the S group. Since they apply themselves more than the other two groups, we would expect better results, lower error rates, when the sequence was simple or not overly complex. But because they are more likely to overextend themselves we would expect a processing system overloading to occur when the sequence was complex. This would result in higher error rates than the other groups. The overloading would in all probability be relatively temporary and in addition non selective in its influencing the two types of errors.

While the preceding is only conjecture, it is consistent with the results in the Colker & Myers and in the present study. It does not, unfortunately, explain why the error rates in training for S and O solvers are lower for complex than for simple sequences. The error frequencies are also less for complex than for simple sequences. At present, there is no good explanation for this phenomenon.

Two additional points should be raised concerning the data. First, while simple and complex training groups' data were each analyzed for the same number of periods, some 2-5 _S_s saw more periods in training than 4-5 _S_s, if they ran the whole 350 trials. In addition, simple and complex training sequences were not analyzed for the same number of periods. The simple sequences were analyzed for 36 periods while the complex ones for [illegible] periods. Second, _S_s trained on complex sequences did not as a group reach the same level of training as the _S_s trained on simple sequences. At the ninth period of the complex training sequences *S*s were, as a group, making significant numbers of Type A and Type B errors. In the simple groups, *S*s had already asymptoted and both of their error rates were at zero percent. It cannot be implied that the complex *S*s' error rates would decrease if they had been run to the same stage of learning as the simple groups, but this factor should be taken into account in the final analysis.

The results of the latency data were not clear cut, but the trends in the position effect seem to indicate some factor working independently of run length since the shape of the position effect curve is the same for both 2-3 and 4-5 groups. There is, however, one technical problem. Latencies were measured from the off set of reinforcement on one trial to the *S*'s response on the next. Since reinforcement lasted one second it is possible that some *S*s might have been able to respond before the situation allowed. If complex groups needed more processing time than simple trained groups there could be a consistent biasing toward the lengthening of simple groups reaction times. The problem is further complicated by the relative time lengths involved between the two groups. We could be getting uniformly truncated reaction times, latencies biased against simple groups, reaction time from which processing time has been eliminated, or reaction times to which random noise has been added. At present it is impossible to know which is the case.

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TABLE 1

NOTATION

Run Lengths	Training Sequence	
	Simple	Complex
	Random	
Two & Five	2-5/S(R)*	2-5/C(R)
Four & Five	4-5/S(R)	4-5/C(R)
	All-Correct	
Two & Five	2-5/S(A)	2-5/C(A)
Four & Five	4-5/S(A)	4-5/C(A)

* Parentheses indicate optional

TABLE 2

t Tests for Homogeneity of Random and All-Correct Groups in Training

Group	Mean Number of Errors	Group	Mean Number of Errors	t
		Type B Errors		
2-5/SA	18 (8.13)[a]	2-5/SR	11.3 (6.33)	2.1561 $p < .05$
4-5/SA	8.6 (3.12)	4-5/SR	12.5 (8.66)	-1.4058 $p < .2$
2-5/CA	32 (19.50)	2-5/CR	29 (11.40)	14404 $p < .7$
4-5/CA	23 (27.69)	4-5/CR	27.7 (19.46)	-.4606 $p < .7$
		Type A & Type B Errors		
2-5/SA	26 (12.18)	2-5/SR	[illegible] (9.55)	[illegible] $p < .2$
4-5/SA	17.75 (5.79)	4-5/SR	23.75 (15.42)	[illegible]
2-5/CA	[illegible] (26.78)	2-5/CR	[illegible] (19.33)	[illegible]
4-5/CA	[illegible] (32.8)	4-5/CR	[illegible]	[illegible]

Note - 22 Degrees of Freedom; 2 Tailed Tests

[a] Standard Deviations in Parentheses

TABLE 5

Pearson Product Moment Correlations
Between Pairs of Raters

Rater	Rater						Mean
	1	2	3	4	5	6	
1	--	.94	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2		--	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3			--	1.0	[illegible]	[illegible]	[illegible]
4				--	1.0	[illegible]	[illegible]
5					--	[illegible]	[illegible]
6						--	[illegible]
					GRAND MEAN		[illegible]

TABLE 4

Number of Simple (S), Complex (C) and Other (C) Protocols for Simple and Complex Training

Training Sequence	Category of Protocol		
	S	C	O
	Mean Rating		
Simple	10.67	1.33	12
Complex	10.33	6.33	7.33
	Consensus Rating		
Simple	10	2	12
Complex	10	7	7

TABLE 5

Numbers of Ss in Simple and Complex
Training Groups Giving Complex or
Noncomplex Solutions Under All-Correct

Training Sequence	Type of Solution Under All-Correct	
	Complex Solutions	Noncomplex (S and O) Solutions
Simple	2	22
Complex	7	17

Note - $\phi = \dfrac{bc - ad}{\sqrt{(a+b)(a+c)(b+d)(c+d)}} = .267,\ p < .05,$

1 tailed test

TABLE 6

Analysis of Variance for
Errors in Transfer

Source	df	MS	F
Type of Training Sequence (T)	1	526.7	3.0[illegible]
Run Lengths Present (R)	1	42.2	2.47
T x R	1	76.0	4.44*
Subjects/T x R	44	17.[illegible]	

* $p < .05$

TABLE 7

Type A and Type B Error Rates in
Training for S, C, and O solvers
For Simple and Complex Training
and Frequencies

Training Sequence	Type of Solution Under All-Correct Transfer		
	S	C	O
	Type A Errors		
Simple	.4595 (.1944)[a]	.3393 (.1607)	.4966 (.0803)
Complex	.41[illegible] (.0703)	.4307 (.0706)	.4961 (.114[illegible])
	Type B Errors		
Simple	.2679 (.1076)	.2112 (.00[illegible])	.262[illegible] (.16[illegible])
Complex	.1042 (.0797)	.2375 (.1276)	.09[illegible]2 (.[illegible]12)
	Frequencies		
Simple	10	2	12
Complex	10	7	7

[a] Standard Deviations in Parentheses

TABLE [illegible]

Analysis of Variance for Latency Data

Variable	Group			
	2-5 Training	4-5 Training	2-5 Transfer	4-5 Transfer
Training Complexity (C)	$F(1,46) = 5.425^a$	$F(1,46) =$ [illegible]	$F(1,22) =$ [illegible].545	$F(1,22) =$ .53[illegible]
Position in Run (P)	$F(4,184) =$ [illegible]	$F(4,184) =$ 1.[illegible]	$F(4,88) = .702$	$F(4,88) =$ [illegible]
Response Type (R)	$F(1,46) = 7.65^c$	$F(1,46) = 3.092$	$F(1,22) = .253$	$F(1,22) = .20.035^b$
C x P	$F(4,184) =$ 3.2[illegible]	$F(4,184) = .26$	$F(4,88) = 1.54$	$F(4,88) = 1.162$
C x R	$F(1,46) = .325$	$F(1,46) = 1.777$	$F(1,22) = 2.4$	$F(1,22) = .033$
P x R	$F(4,184) = 1.633$	$F(4,184) = 1.98$	$F(4,88) = .548$	$F(4,88) = 11.162^b$
C x P x R	$F(4,184) = 2.166$	$F(4,184) = .654$	$F(4,88) = 1.38$	$F(4,88) = .162$

[a] $p < .025$

[b] $p < .001$

[c] $p < .01$

TABLE 9

Mean Latencies for Run Position*
by Group in Seconds

Group	Position in Run				
	1	2	3	4	5
[illegible]-5 Training	.20[illegible]5	.1[illegible]	.17[illegible]2	.17[illegible]	[illegible]
4-5 Training	.1[illegible]4[illegible]	.15[illegible]	.1[illegible]4[illegible]	.17[illegible]4	.1[illegible]7
2-5 Transfer	.212[illegible]	.15[illegible]	.1[illegible]	.1415	.16[illegible]3
4-5 Transfer	.120[illegible]	.1[illegible]17	.19[illegible]	.1[illegible]	.1[illegible]11

* Position = Number of events seen in current run